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Hybrid approaches in Network Optical Routing with QoS based on Genetic Algorithms and Particle Swarm Optimization

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***Abstract*—Hybrid heuristics have been proposed by many researches as a method to overcome problems in pure heuristic implementation for multi-constrained QoS routing problems. In this paper we present some hybrid approaches based on Genetic Algorithms and Particle Swarm Optimization as well as their performance to solve NP-complete routing problem. .**

***Index Terms*—PSO, GA, Routing, Multicast, Anycast, Optimization.**

I. INTRODUCTION

Today's networks are rapidly increasing the amount and type of transported traffic. Every service has different restrictions based on the state of the network, such as: bandwidth, delay, jitter, loss packet rate. Therefore, routing mechanism relying on those constrains are necessary. But, finding multiple paths with multi-constrained QoS requirements has been proven to be NP-complete [1]. Hence, multiple heuristic has been proposed to solve the problem such as Ant Colony Optimization (ACO), Simulated Annealing (SA), Genetic Algorithms (GA), Particle Swarm Optimization (PSO) [2]. Nevertheless, pure heuristic implementation has shown some lacks and then hybrid models are presented. In the same way, different routing approaches has been introduced to make easier the routing problem such as multicast and anycast routing [3,4] and some kind of algorithms for each one of the routing approaches. The actual work presents some hybrid approaches based on Genetic algorithms and Particle Swarm Optimization and different mixing ways to solve multi-constrained routing problem. Furthermore, performance and simulation results are presented comparing pure heuristic and hybrid approaches.

II. BIO-INSPIRED MODELS

A. Genetic Algorithms.

The heuristic proposed by Holand in 1970 [5] based on the Darwinian evolution theory, has been used to solve optimization problems, although, it has been applied to different fields such as trust models in MANET's [6], Bandwidth calculation [7], Gas-lift Allocation [8], Differential calculus [9], Robotics [10], Mobiles [11], Smart Antenna Systems [12], Networks design [13], IDS [14], Load Balancing [15], Vehicle routing [16], Signal processing [17], Neuronal networks [18]. T

he method relies on genes, chromosomes and their interaction. In order to exchange information between chromosomes, GA (Genetic Algorithms) uses some genetic operators called: Crossover, Mutation and Selection. A set of genes make up a chromosome which represents possible solution to a problem. The interactions between chromosomes are called Crossover. Selection is used to filter individuals (chromosomes). It bases on a "fitness" value witch allow to select the stronger ones. Many selection approaches has been proposed such as: *proportionate selection scheme* [19] where the fitness function uses the average fitness value within the whole population and divides it with chromosome fitness value. This method allows selecting only the chromosomes which have a higher fitness value than population average fitness as in (1).

$$\frac{f_i}{\bar{f}} \qquad \text{Where}: f_i = \text{Chromosome fitness} \qquad (1)$$

$$f_i = \frac{\sum_{i=1}^{n} f_i}{n}$$

In *roulette wheel selection* [19] a roulette wheel is adopted for the chromosomes, each of them, has a part of the angle within, a number is randomly generated from 0 to $2\pi \frac{f_i}{\bar{f}}$ and if it falls in the chromosome space it is elected. Other approaches have been proposed [20]. Mutation operator relies on a mutation rate, which allows changing information from the chromosomes randomly and sporadically. It is used to escape from local optimal. Selection GA parameters has been studied by different researchers (De Jong, Grefenstette, Bäck, Gao) as explained in the section *selecting GA parameters* in [21]. Finally, due to the complex computational resources used by GA, Parallel Genetic Algorithm has appeared as a possible solution for this issue [22, 23, 24]. The GA process is showed Fig.1 part (a).

B. Particle Swarm Optimization.

Social behavior is the base of PSO (Particle Swarm

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Optimization) heuristic. Based on bird flocking, fish schooling and particularly swarming theory, James Kenedy and Rusell Eberhart proposed PSO in 1995 [25] simulating bird flocks looking for corn. The approach is similar to Genetic Algorithms. In PSO the individuals are called particles. Unlike to GA, PSO does not rely on genetic operators; In order to find the best solution the particles follow the best particle found so far and evaluate which particle is placed in a better position (solution) in the problem space (closer to the global optimal function value).The evaluation bases on three vectors attached to each one of the particles: current position ($\vec{x_i}$), previous best position $(\overrightarrow{pbest_i})$ and velocity ($\vec{v_i}$). When a better position is found, the value (coordinates) is stored in the $(\overrightarrow{pbest_i})$ vector (fitness). The vector (*vi*) describes the next movement of the particles and it is achieved by adding the ($\vec{v_i}$) coordinates to ($\vec{x_i}$) vector, the equations for ($\vec{v_i}$) vector and the ($\vec{x_i}$) update position are described in (2). The best position found by the heuristic is stored in a previous best vector $(\overrightarrow{gbest_i})$ .The interaction among the particles is the main factor in the heuristic successful. Thus c_1 is a cognitive constant, which means every particle tends going to its better known position $(\overrightarrow{pbest_i})$, and C_2 is a social constant, which means every particle tends going to the better know position within the whole particle population $(\overrightarrow{gbest_i})$ [26]. In [27] the authors improved PSO and included a inertia weight ω ,which means a energy loss while moving, "can be interpreted as the fluidity of the medium in which a particle moves [27]", researches have found a relation: when applying $\omega = 0.9$ the exploration is higher, due to the easy particles movement, and lower exploration with $\omega = 0.4$, due to high viscosity medium [28].PSO has many applications in different fields such as: antennas, biomedical, networking, control, as described in [29]. Finally, some test functions are proposed in chapter 4 "Benchmark Set" in [30]. The initial PSO pseudo-code is presented in Fig.1 part (b).

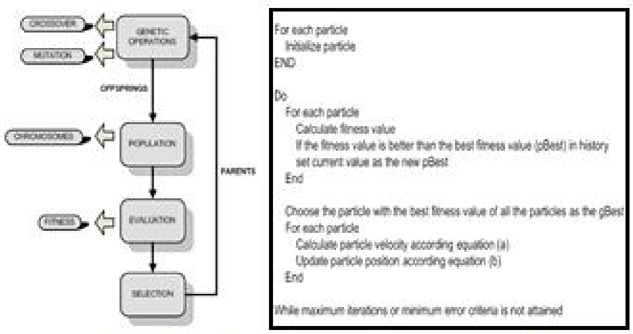
III. HYBRID APROACHES

Based on GA and PSO features, many researches have performed comparison studies. Results show the integration of this heuristics is a good approach [31,32,33]. PSO has an easy implementation, low computational cost, memory and rapid convergence [34], while GA are slow to convergence, require a higher computational cost and every generation the memory is erased, but its genetic operator achieve better fitness value, helping to escape from local optimal. Different implementation approaches have been proposed, this section is intended to show some of them and generally describe the way researches mix the heuristics to solve multi-constrained QoS routing problem.

$$\left\{\begin{array}{l} \bullet\ \vec{v_i}[] = \vec{v_i}[] + c1 * rand() * \left(\overrightarrow{pbest_i}[] - \vec{x_i}[]\right) \\ + c2 * rand() * \left(\overrightarrow{gbest_i}[] - \vec{x_i}[]\right) \ (a) \\ \bullet\ \vec{x_i}[] = \vec{x_i}[] + \vec{v_i}[] \ (b) \end{array}\right\} \tag{2}$$

where

- $\vec{v_i}[]$ *is the particle velocity*
- $\vec{x_i}[]$ *is the current particle*
- *pbest[ ] and gbest[ ] are defined stated before*
- *rand( ) is a random number between (0,1)*
- *c1 and c2 are learning factors, usually c1 = c2 = 2*



(a).Genetic Algorithms Cycle (b). Pseudo-code of initial PSO [35]

Figure 1. Bioinspired Cycles

A. PSO - GA chromosome.

The hybrid proposed in [36] for multicast routing with QoS, bases on the fact, GA initial chromosomes are randomly generated. Hence, the algorithm convergence becomes slower. In order to overcome the shortcoming a hybrid based on GA-PSO is presented. The new algorithm performs PSO in the route generation from source node to each destination node, which means PSO, is used in the initial GA chromosome generation. In order to select the routes which will be included the chromosomes a probability matrix is proposed. Therefore, initial population is elite for GA and convergence can be achieved in less iterations. After chromosomes based on PSO are generated, the GA heuristic tries to find the minimum cost multicast tree. Simulation is implemented in NS2 and comparison between pure GA and hybrid approach as shown in Fig.2 parts (a-b).

B. PSO - elite group chromosome.

Another approach proposed by Changbing Li, Changxiu Cao1, Yinguo Li and Yibin Yu' in [37] for multicast routing with QoS problem, relies on the GA improvement, the hybrid is performed by initial GA heuristic, when the chromosomes are created, the upper-half of the best fitness chromosomes is selected and called elite group, in this phase PSO heuristic

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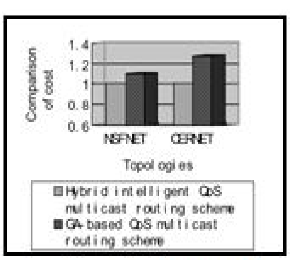
is performed, then, elite group will be tread as a swarm, each one of the elites in the group will be particles as in PSO, the elites are enhanced by PSO, finally reproduced and selected as parents for crossover in GA. The proposed method is in accordance of the authors as the growing up and adaptation to the medium that individuals perform before reproduction. In normal GA heuristic the chromosomes are immediately reproduced without this approach. The proposed algorithm is called HGAPSO. As described in the paper, better results are achieved by the hybrid approach optimizing cost of the tree, max end-to-end delay, average delay and max link utilization as presented in Fig2 part (c-e) and table I.

C. GA Genetic Operator - PSO

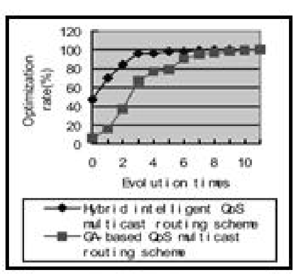
The method proposed by LI Taoshen, XIONG Qin and GE Zhihui in [38] for anycast Routing with multi-constrained QoS restrictions problem is based on the integration to genetic operator from GA to PSO, as described before PSO has a rapid convergence but it is easy to fall in local optimal, then, genetic operator are used to solve the shortcoming. The method initially performs PSO in the routing algorithm with a group of random particles which search for an optimal fitness, the update operator in PSO is improved in order the particles to learn about sub-routes within other particles, in this way the particles learn about better sub-routes and they become better, when PSO gets in a local optima crossover and mutation operators are performed. Thus, PSO can escape from local optimal and achieve better solutions. Simulations presented in the paper showed better fitness values for hybrid approach and less iterations for convergence than pure heuristic approaches as described in Fig. 2 part (f).

IV. Bioinspired models in optical networks

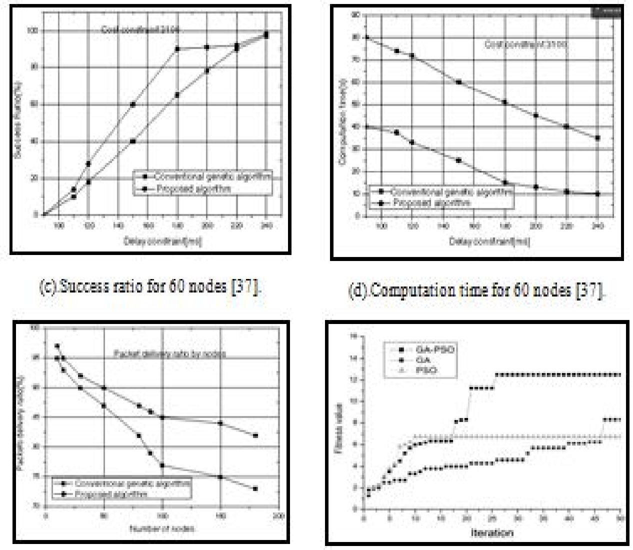
The implementation of routing approaches described before try to address the multi-constrained QoS problem in the network layer. In the other hand, it could be useful to extend QoS constrains to physical layer. Bio-inspired models have been also proposed to solve WDM (Wavelength Division Multiplexing) problems, where the use of optical fiber bandwidth is intended to be optimized by using non-interferencing channels with multiple carriers at different frequencies. GA is applied to improve routing with optical networks [39], where a lightpath could be created based on the connection request of a specific service. This approach allow to improve QoS constrains, due to its implementation not only in network layer but also in physical layer.



(a). Comparison of multicast tree cost[36].



(b). Relationship between optimization Rate and evolution times [36].



(c).Success ratio for 60 nodes [37].

(d).Computation time for 60 nodes [37].

(e).Packet deliver ratio for different nodes [37].

(f). The fitness changes with the iterations [38].

Figure 2. Hybrid Performance

TABLE I. . Comparison of proposed algorithm and conventional algorithm with the mean percentage deviations [37].

Number of nodes	Optimal Solution	Mean percentage Deviation (std) (%)	
		Proposed Algorithm	Conventional Genetic Algorithm
10	252	2,87(4,07)	2,68(5,12)
15	316	6,36(6,12)	18,82(8,79)
39	472	5,86(4,17)	45,36(12,26)
50	668	3,17(2,88)	73,62(10,95)
80	988	3,68(1,07)	212,36(21,46)
100	1262	2,14(0,66)	252,70(12,58)
200	2168	9,38(1,26)	412,67(10,37)

Conclusions

Different kind of heuristics have been used by researches to solve routing problem, the paper described different approaches in hybrid application models based on Genetic Algorithms and Particle Swarm Optimization. The simulation results have proven hybrid heuristics to achieve better performance than single heuristic implementation, due to implementation of heuristics features to overcome lacks in heuristics such as slow convergence time or local optimal. Furthermore, different mixed forms have been shown for same hybrid approach.

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